Neuro-Fuzzy-Based Crowd Speed Analysis at Mass Gathering Events

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ABSTRACT

Airports, shopping centers, sport stadiums and religious houses,… etc. are largely crowded areas. There is a need for the design and planning of crowded facilities to handle large volumes of crowd. Injuries and fatalities in emergency evacuations were not only caused by the hazards, but also by actions of the crowd. Stampedes are caused both by the real hazards like fire, earthquake,… etc. and the behavior of the crowd. Crowd speed is one major factor in analyzing crowd events. The physical factors and environmental factors influence the speed of an individual in a crowd. In this study, effects of factors like age, gender, group size, child holding, child carrying, people with luggage and without luggage on crowd speed are considered for analysis. The statistical analysis concluded that there was a significant effect of age, gender, density and luggage on the crowd walking speed. Multi-linear regression (MLR), Artificial Neural Networks (ANNs) and Adaptive Neuro-fuzzy Inference System (ANFIS) models were developed between crowd speed and significant factors observed from the statistical analysis. The results showed that the ANFIS model results are the best fitted compared to other models. The Mean Absolute Percentage Error (MAPE) and Route Mean Square Error (RMSE) of the ANFIS model are determined as 0.130 and 0.098.

KEYWORDS: Crowd, ANN, ANFIS, MLR, RMSE, MAPE, Speed.

INTRODUCTION

A mass gathering is "*when more than a specified number of persons at a specific location for a specific purpose gather for a defined period of time*" (WHO, 2008). Understanding and modeling how persons behave individually and in groups in various situations can help crowd events become safer. Mass gathering events have a massive potential to place a severe disaster on the crowd. High crowd density, lack of crowd control, constrained points of access and lack of complete information of crowded areas can lead to disasters (Soomaroo et al., 2012). Mass gatherings can be sport events, political rallies, concerts, religious gatherings,… etc. Among these, religious gatherings are quite common in India and some other countries. Crowd behaviour analysis helps in many ways to understand crowd dynamics and people behaviours. It can help develop and design crowd control systems and organize public spaces.

Crowd behaviour analysis is divided into two types, which are the object-based approach and the holistic-based approach (Mehran et al., 2009). In the object-based approach, crowd is considered as a collection of individuals and detecting the individuals is used to analyze the group behaviour. This method is applicable to low and moderate crowds and not applicable to denser

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crowds, because it is very difficult to track individuals in high-density crowds. Holistic-based approach treats crowd as a single unit. This approach ignores the information such as a person moving against the flow. This method is mostly applicable to densely crowded scenes. Crowd is divided into two types, which are structured crowd and unstructured crowd based on the motion of the crowd (Rodriguez et al., 2009). In structured crowd, crowd moves systematically in a common direction and the flow path does not vary with time. Meanwhile, in unstructured crowd, different persons move in different directions at different times.

Generally, in the crowd, different age groups of persons, gender variations, group sizes, child carrying, child holding and people carrying luggage are present. The proportions of the above categories will affect the crowd behaviour. Therefore, it is essential to understand the effects of crowd characteristics, like age, gender, luggage,… etc. on crowd speed. In this study, the object-based approach is used to analyze the crowd behaviour with the factors mentioned above (gender, age, group size, child carrying, child holding and luggage).

Review

There are several ways to analyze the crowd, including crowd density estimation and crowd tracking. For density measurement, object detection technique is used, whereas for speed, object tracking technique is used. MLR, ANN and ANFIS models are used in order to model crowd speed.

Detection

Object detection is the process of finding objects (people, faces, vehicles,… etc.) in images or videos. Background subtraction, optical flow and spatio-temporal filtering methods were used for object detection. Background subtraction method tries to detect moving objects from the video based on the difference between current frame and reference frame (background image). Mixture of Gaussian model (Stauffer et al., 1999; Lee et al., 2005), non-parametric background model (Kim et al., 2012; Elgammal et al., 2003), temporal differencing (Cheng et al., 2011), warping background (Ko et al., 2010) and hierarchical background (Chen et al., 2012) approaches were used in background subtraction method. Optical flow is a vector-based approach (Candamo et al., 2010; Xiaofei et al., 2010) that estimates motion in video by matching points on objects over frames. In spatio-temporal filtering method, motion is recognized based on spatio-temporal analysis. The motion of the person in the image sequence is described *via* 3D spatio-temporal data volume (Zhong et al., 2004; Piroddi et al., 2006). Optical flow methods have disadvantages compared to background subtraction, because they require higher computational time and special hardware for real-time applications (Candamo et al., 2010). Spatio-temporal filter works well for low-resolution scenarios, but it suffers from noise issues. Background subtraction method is good in outdoor environment with high background motion. In this study, the background subtraction technique is used for object detection.

Tracking

Object tracking is defined as the tracking of objects over a sequence of frames in a video. Object tracking techniques can be classified as point tracking, kernel-based tracking and Silhouette-based tracking. Point tracking method detects objects in successive frames represented by points. There are three methods to track objects based on point tracking; these are Kalman filtering (Joshan et al., 2012), particle filtering (Liang et al., 2007) and Multiple Hypothesis Tracking (MHT) (Lee, 2005). Kernel tracking is performed by locating the moving object that is represented by a developing object region, from one frame to the subsequent one (Joshan et al., 2012). There are four methods to track persons based on kernel-based tracking. These are simple template matching tracking (Huang et al., 2012), mean shift tracking (Samuel et al., 2004), support vector machine (Kim et al., 2010) and layering-based tracking (Mishra et al., 2012). Silhouette-based object tracking is to find the object region in every frame by using an object model generated by the previous frames (Joshan et al., 2012). There are two methods to track persons based on Silhouette-based object tracking, which are contour tracking (Joshan et al., 2012) and shape matching (Joshan et al., 2012).

In this study, crowd tracking is done by using TRACKER software. It is a semi-automatic method, which is useful when crowd size is very high and helpful when obstructions are present in the study area. While converting pixels into real-world coordinates using a calibration stick, it gives some errors. Therefore, a direct linear conversion algorithm was applied based on Wolf and Dewitt to minimize the effect of swaying and height difference (Wolf et al., 2000).

Modeling

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a "*mathematical model, which can be set one or more layered and consists of many artificial neural cells*" (Jang et al., 1997). The extensive usage of ANNs may be due to the ability of the ANN parallel processing of problems, generating forecasts from historical data extrapolation and application to solve nonlinear problems. Florio et al. (1996) evaluated the flow–density relationship of a motorway section to define the time and spacing stability or instability of its motorized traffic flow. Dougherty et al. (1993) and Smith et al. (1994) focused on traffic flow prediction based on the ANN approach. Kumar et al. (2013) used the ANN approach to develop a short-term prediction of traffic volume using past traffic data on NH-58. Sahani et al. (2014) used ANN clustering to define LOS levels. There are several difficulties that have been encountered in the ANN modeling approach, where the overfitting problem is one of the important difficulties taking place if data is not proportionally divided as training, testing and validation. In this study, the ANN approach is used for the development of a relationship between crowd speed and factors affecting crowd speed.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Zadeh (1965) is the first person who introduced the fuzzy logic concept. After Zadeh, many researchers developed models using the fuzzy logic approach in different areas. The primary advantage of the fuzzy logic approach lies in its attractive features, like simplicity and natural structure. Pappis et al. (1977) conducted a study on the implementation of a fuzzy logic controller in a single intersection of two one-way streets using average delay as the performance criterion. Teodorovic et al. (1990) applied fuzzy set theory to solve the problem of traffic assignment between two alternative routes on a highway network.

The membership functions and rule base are determined by trial and error based on fuzzy modeling. In this method, determination of best fitting limits of membership functions and number of rules is challenging. To overcome this difficulty, neural networks have been employed in fuzzy modeling. This system has been called a neuro-fuzzy or adaptive network-based system. The main advantages of neuro-fuzzy systems are accurate learning capabilities of neural networks, combined with simplification and fast learning abilities of fuzzy logic systems. Jang (1992) developed an Adaptive Network-based Fuzzy Inference System (ANFIS). Rong et al. (1996) developed an algorithm using FNN to extract fuzzy rules directly from numerical examples. Rojas et al. (2000) presented a methodology to automatically identify the structure and optimization of parameters using a three-phase approach to construct a fuzzy system. Ouyang et al. (2000) proposed a hybrid algorithm that can automatically extract fuzzy rules from a set of numerical data points. Guler et al. (2004) presented a new approach based on ANFIS for detection of electrocardiographic changes in patients with partial epilepsy.

The present study analyzes the effect of gender, age group, group size, child carrying, child holding and people with and without luggage on crowd behaviour. In the present study, density is estimated by background subtraction and speed by tracker software. Linear (MLR) and nonlinear analyses (ANN, ANFIS) have been conducted on crowd speed using the above mentioned factors.

Study Area and Data Collection

Sammakka - Sarakka festival in Medaram, Warangal city, Telangana, India is selected for conducting the study. This event was held during the 17th to 20th February 2016. Sammakka-Sarakka festival is the Hindu largest tribal congregation in the world and the second largest in India after Kumbha Mela (120 million people in approximately 30 days). This festival is held every two years with approximately ten million people over a period of four days. Data is collected using video-graphic survey. Video-graphic data had been collected for four hours under normal weather conditions. Video extraction was done for 9000 frames and 320 samples were collected. The extracted data was categorized due to gender (male and female), age group (child, young, middle and elder), group size (2 and 3+), child holding (CH), child carrying (CC) and people with and without luggage. From the video parameters, people count and tracking of individuals were extracted.

METHODOLOGY

The methodology followed in this study includes data collection, data extraction, density estimation and identification of factors affecting crowd behaviour, speed and flow estimation, thereby analysing crowd speed affected by those factors using MLR, ANN and ANFIS methods. The collected video is played in the lab and data extraction is presented in detail in the subsequent sections.

Crowd Density Estimation

For crowd density estimation, the background subtraction method is used. In this method, two images are imported which are the reference image and the actual image. In the background subtraction method, input image is converted from RGB into gray and compared with the reference image to find the difference. Later, the image is converted into a binary image and blobs are detected. These blobs represent the number of people in the image. The ratio of people count to area gives the crowd density. The next section describes the process of crowd tracking using tracker software to extract the speed of persons in the crowd.

Crowd Tracking

In crowd analysis, another task is tracking the people, which includes identifying the position of the same person in a sequence of frames. Figure 1 shows the image tracking of persons in the frame. For analysis, tracker software is used, where the persons are tracked manually as well as automatically to find position, velocity and acceleration.

For the extraction of speed, the video is imported into the tracker software, where the tracker automatically converts the video into frames. After converting the video into frames, the coordinate axis needs to be fixed and the point mass is to be created. Subsequently, when persons in the crowd are selected manually, the coordinates and the speed of the selected person are observed automatically.

Figure (1): Image representing tracking of persons (sample)

The pixel coordinates obtained from the video could not represent person movements in real-world situations, because the camera angle was not perpendicular to the ground. Hence, conversion of pixel coordinates into real-world coordinates was required for getting the real-world trajectories of individuals. A direct linear conversion algorithm was applied based on

Wolf and Dewitt (2000). The relevant conversion formulae are as follows (Eqs. (1) and (2)):

$$u + \frac{T_1 x + T_2 y + T_3}{T_7 x + T_8 y + 1} = 0 \quad (1)$$

$$v + \frac{T_4 x + T_5 y + T_6}{T_7 x + T_8 y + 1} = 0 \quad (2)$$

where (u, v) are the pixel coordinates, (x, y) are the real-world coordinates and T_1–T_8 are transformation coefficients. Eight real-world reference points are selected and measured in the experiment along with the corresponding pixel coordinates. Four points are used to compute the conversion coefficients and the remaining four points are used to check the errors. The following section describes the results and discussion.

Analysis

The average speed, density and flow are observed as 0.703 m/sec, 1.73 P/m^2 and 73 P/min/m, respectively. The average speed of a male person is as high as 0.903 m/sec as compared to that of a female person with 0.736 m/sec. The speed of a person without luggage is 1.014 m/sec as compared to that of a person with luggage amounting to 0.85 m/sec. The average speed of a younger person is as high as 1.173 m/sec compared to the average speeds of other age groups. The average speed of CH is as high as 0.915 m/sec as compared to that of CC with 0.85 m/sec. The speed of three or more persons in a group was low compared to single and paired persons. Table 1 represents the comparison of crowd speed with respect to gender, age, group size, CC, CH, people with luggage and people without luggage.

From the table, it can be observed that the speed of younger male persons without luggage was high, that of elder female persons with luggage was low and that of younger male persons with luggage was medium. These observations for various crowd categories were used in creating rules in the ANFIS analysis.

Table 1. Comparison of crowd speed due to different factors

			Average speed (m/s)
Child	Male	With luggage	0.835
		Without luggage	1.21
	Female	With luggage	0.70
		Without luggage	0.83
Young	Male	With luggage	0.932
		Without luggage	1.5
	Female	With luggage	0.89
		Without luggage	0.99
Middle age	Male	With luggage	0.924
		Without luggage	1.13
	Female	With luggage	0.79
		Without luggage	0.853
Elder	Male	With luggage	0.72
		Without luggage	0.86
	Female	With luggage	0.61
		Without luggage	0.74
Child carrying	Male		0.93
	Female		0.78
Child holding	Male		0.98
	Female		0.85
Group	Two		0.91
	>Three		0.83

Multi-linear Regression Analysis

For statistical analysis, ANOVA and Pearson correlation tests were performed using SPSS and the variables considered for analysis were: gender, age group, group size, CH, CC and person with luggage and person without luggage. Gender was divided into two categories and the values were assumed as 0 for male pedestrian and 1 for female pedestrian. Age was divided into four categories and the values were considered as 0 for the child, 1 for younger, 2 for middle age and 3 for elder. The values due to luggage carrying were assumed as 0 for people without luggage and 1 for people with luggage. CH was divided into two categories and the values were considered as 0 for not holding children and 1 for holding children. CC was divided into two categories and the values were assumed as 0 for not carrying children and 1 for carrying children. Group size was divided into three categories; 0 for single, 1 for pair and 2 for more than three persons.

All tests are performed at 95% confidence level. From Table 2, it can be seen that gender, age, group size and luggage are factors that have significant effects on pedestrian walking speed. The F-value is higher than the table value (3.842) and the P-value is less than 0.05 for all factors. Pearson correlation coefficient value ranges between -1 and + 1. where -1 shows total negative correlation, 0 indicates no linear correlation and +1 shows total positive correlation. Pearson correlation coefficients were found to indicate negative linear correlation for gender, age, luggage and density. A nonlinear correlation was observed for CC and CH with respect to speed.

Table 2. Statistical tests for crowd movement

Factor	ANOVA		Pearson Coefficient		Remarks
	F	P-value	Coefficient	P-value	
Gender	191.111	$5.07\text{x}10^{-37}$	-0.527	$5.07\text{x}10^{-37}$	Significant
Age	53.963	$3.35\text{x}10^{-30}$	-0.328	$5.12\text{x}10^{-14}$	Significant
Luggage	68.193	$1.11\text{x}10^{-15}$	-0.333	$1.116\text{x}10^{-15}$	Significant
CC	2.759	0.0972	-0.071	0.0972	Not significant
CH	0.905	0.342	0.041	0.342	Not significant
Group	1.097	0.312	-0.034	0.540	Not significant
Density	16.041	$3.10\text{x}10^{-06}$	-0.163	0.0218	Significant

The general form of the linear regression model suggested is:

$$Y = A_1X_1+A_2X_2+\ldots+A_kX_K+\varepsilon \quad (3)$$

where Y = crowd speed, X_1= gender, X_2 = age, X_3 = luggage, X_4 = density, A = parameter, ε = constant.

For the current study, a regression analysis is applied to the crowd movement as tabulated in Table 3. Negative values of β are obtained which will significantly decrease the speed with every increase of the following parameters: children, female, persons with luggage and density. Pedestrian gender has more effect on the speed of the crowd compared to other factors, because the coefficient of gender is more compared to other factors. The observed speed and estimated speed values using MLR are plotted in Figure 2.

The regression expression is obtained as:

$$\text{Speed} = 1.171-0.242 \times \text{gender} -0.070 \times \text{age} - 0.179 \times \text{luggage} -0.150 \times \text{density} \quad (4)$$

Table 3. Regression analysis for crowd speed

Model	β	Standard Error	Significance
Constant	1.171	0.015	0.000
Gender	-0.242	0.012	0.000
Age	-0.070	0.006	0.000
Luggage	-0.179	0.014	0.000
Density	-0.150	0.022	0.000

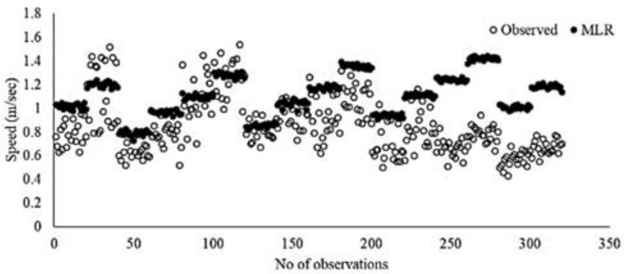

Figure (2): Comparison between observed and MLR speed values

ANN

In this study, the ANN approach is adopted to develop a model using parameters affecting crowd speed. Four ANN models were developed using NN tool in MATLAB and the details are given in Table 4. From Table 4, the ANN 3 model gives better performance as compared to the other three ANN models in terms of R-value and MSE. Architectural view of a typical neural network is shown in Figure 3. Graphical representation of observed and ANN3 model crowd speed values is shown in Figure 4.

Table 4. Performance of ANN models

Model	No of Neurons	R	MSE
ANN 1	5	0.8535	0.0206
ANN 2	10	0.8445	0.0198
ANN 3	15	0.8489	0.0183
ANN 4	20	0.8423	0.0194

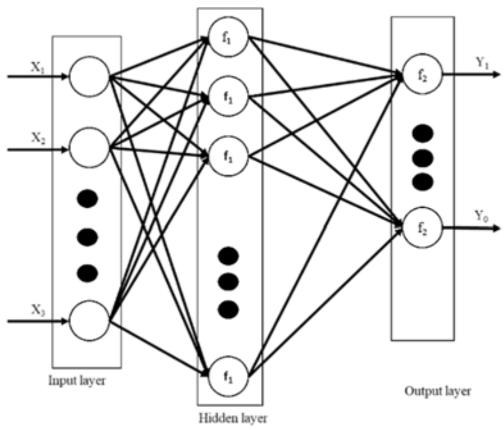

Figure (3): Architecture of neural network

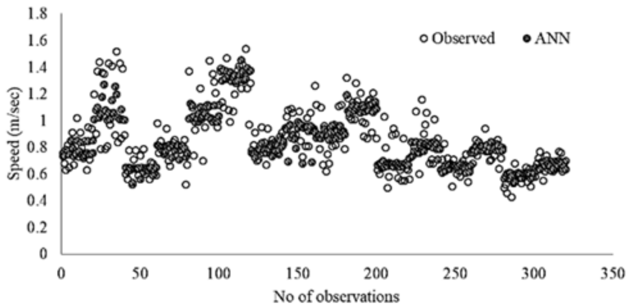

Figure (4): Comparison between observed and ANN speed values

ANFIS

Jang (1992) developed an Adaptive Network-based Fuzzy Inference System (ANFIS) and used it with the fuzzy logic toolbox of Matlab software. Before constructing the ANFIS model, select input and output variables and divide the data into training and checking datasets. Gender, age, density and luggage variables are considered as independent variables and speed is considered the dependent variable for this modeling. The collected data was divided randomly into a training dataset (80%) and a checking dataset (20%). For building the ANFIS model, the training dataset was assigned. The checking dataset was used to avoid overfitting of the system to the training dataset.

ANFIS model construction involves two steps which are fuzzification and training. The main aim of fuzzification is to establish an initial fuzzy inference system. The ANFIS model structure is selected by determining the number, type and shape of membership functions per input variable. The next step is training the parameters in order to minimize RMSE and adjust the shape of the membership functions. The ANFIS model is developed based on a hybrid algorithm. This algorithm consists of backpropagation for the parameters associated with the input membership functions and least square estimation for the parameters associated with output membership functions.

ANFIS uses simultaneously training and checking datasets to avoid overfitting. Training of the ANFIS may be stopped by two measures. In the first measure, the learning process will be stopped when the training data error remains within the tolerance. In the second measure, the learning process will stop when a maximum number of iterations (epochs) is achieved. In this study, ANFIS training is stopped if the error tolerance is near to 0 or if the number of training iterations reaches 100, whichever comes first. The best ANFIS model is selected based on achieving a minimum RMSE for both training and checking datasets. The constructed fuzzy model with four inputs, 3 rules and one output is shown in Figure 5. The constructed ANFIS model is shown in Figure 6 and the 3 rules created are summarized in Table 5. Rules are created based on the results observed from Table 1. For example, speed of younger male persons without luggage was found to be high, that of elder female persons with luggage was low and that of younger male persons with luggage was medium. The model structure has a total of 12 nodes (3×4) for Layer 1, three nodes for Layer 2 and three nodes for Layer 3, representing the parameters of the linear function. Figure 7 shows the input membership functions of the ANFIS model. The 3D diagram of the training data is shown as the target surface in Figure 8.

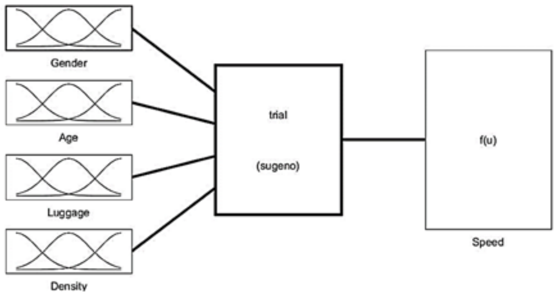

Figure (5): Fuzzy model construction

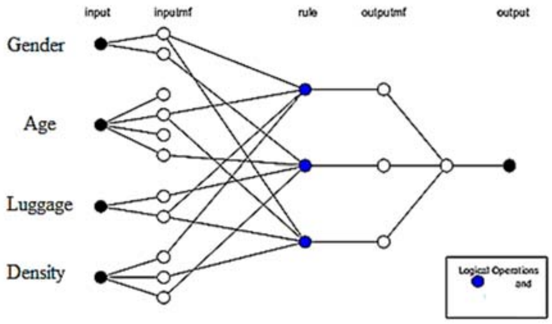

Figure (6): ANFIS model structure

Table 5. Constructed rules for ANFIS model

Rule No.	Rule
1	If gender is male, age is young, luggage is without and density is low, then speed is high.
2	If gender is female, age is old, luggage is with and density is high, then speed is low.
3	If gender is male, age is young, luggage is with and density is medium, then speed is medium.

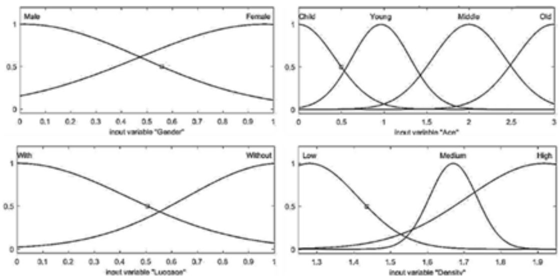

Figure (7): Input membership functions

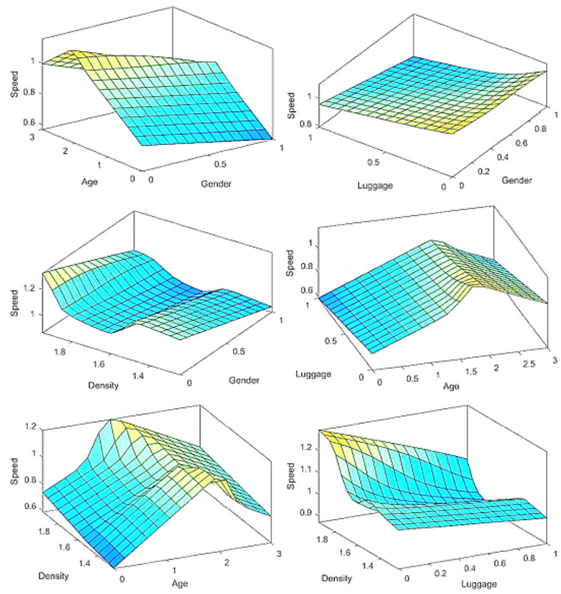

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Figure (8): 3D diagram of training data

The linguistic labels male and female are assigned to gender, while child, young, middle age and old are assigned to age. With and without labels are assigned for luggage and low, medium and high labels are assigned to density. The estimated parameters of the output functions are demonstrated in Table 6. Figure 9 shows the observed, MLR, ANN and ANFIS model speed data.

The estimated consequent parameters of Sugeno linear function are expressed as:

$$V_i = G \times p_i + A \times q_i + L \times r_i + K \times s_i + t_i \quad (5)$$

Table 6. The output parameters of Sugeno linear function

Membership	p_i	q_i	r_i	s_i	t_i
Low	0.264	-0.134	-0.241	-0.229	1.110
Medium	-0.193	0.270	0.550	0.129	0.620
High	-0.166	0.164	0.610	-1.753	2.724

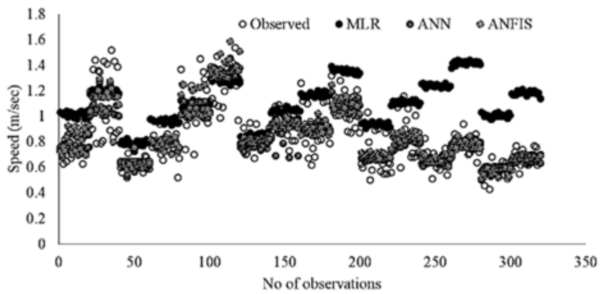

Figure (9): Comparison of MLR, ANN and ANFIS speed with observed speed

Validation

Validation is an essential part of modeling which shows that the model is a realistic representation of the actual data. MAE (mean absolute error) and RMSE (root mean square error) are used to check the accuracy of model prediction. MAE states accuracy as an error, whereas RMSE is used to measure the difference between the estimated value and the observed value. The model with less MAE and RMSE is considered to be the best prediction model. MAE and RMSE values were calculated using Equation (6) and Equation (7). The RMSE and MAE values for the developed models are given in Table 7.

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i-E_i}{O_i}\right| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i-O_i)^2}{N}} \tag{7}$$

Table 7. Accuracy measurements for model validation

Model	RMSE	MAE
MLR	0.343	0.391
ANN	0.137	0.101
ANFIS	0.130	0.098

It can be observed that RMSE values are less than 0.5 and ANFIS model RMSE value is less compared to the other models. Hence, it can be concluded that the ANFIS model is the best-fitted model for the observed data in the validation process.

Discussion

From Table 7, the variables gender, density and luggage have a negative effect, while age has a conflicting effect on the speed of the crowd. More details regarding the effect of each variable are explained in the following part.

Gender

Gender is found to decrease the speed of the crowd because of the number of female persons in the crowd which leads to speed reduction. Generally, the speed of a female person is lower compared to that of a male person, especially in religious gatherings because of female costumes.

Density

Density is found to have an adverse effect on speed. At low crowd density, the speed of the crowd was high due to fewer interactions between persons and more space for overtaking. The speed was low at high crowd density because of more interactions between persons, less space for overtaking and dynamic lanes formed.

Luggage

Luggage is also found to have an adverse effect on crowd speed. The speed of people with luggage is lower compared to that of people without luggage. In religious gatherings, crowd density is high and the number of people carrying luggage is more; so, the speed of a person with luggage is lower when compared to that of a person with normal walking speed.

Age

The relation between speed and age seems to be somewhat conflicting. The results of the ANFIS model show that the effect of age on crowd speed varies. Children and old persons are negatively associated with crowd speed. When the number of children and old persons increases, the speed of the crowd decreases. On the other hand, younger and elder persons are positively associated with the crowd speed. The speed of the crowd is higher when the number of younger and elder persons is more.

CONCLUSIONS

Religious occasions, gatherings at fairs and gatherings at terminals are events of crowd gatherings. Such gatherings act as severe threats for crowd due to high density in less space, which ends up in adverse outcomes resulting in crowd stampedes. The present study focuses on the behaviour of individuals in the crowd. Crowd density was estimated using foreground detection using background subtraction method and crowd speed was estimated using tracker software. It was observed that the average crowd density was 1.73 p/m^2 and the average speed of the crowd was 0.703 m/s, respectively. From statistical tests, it was concluded that gender, age, density and luggage factors affect the pedestrian walking behaviour significantly. MLR, ANN and ANFIS models were developed for the modeling of crowd speed using the factors considered. The developed model is validated using RMSE and MAE values. Based on RMSE and MAE values, ANFIS model is the best-fitted model compared to the other models. This study helps in finding a proper dispersal of the crowd in a planned manner instead of diversified directional flows that exist during crowd gathering events.

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